ANALYSTS' FORECASTS AS EARNINGS EXPECTATIONS

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WP #1743-86 1985 December 1985

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Second Draft

Comments Welcome

This paper is based on work included in my doctoral dissertation. I am grateful to the members of my committee, John Abowd, Craig Ansley, Nicholas Dopuch, Richard Leftwich, Victor Zarnowitz, Mark Zmijewski, and especially Robert Holthausen, for their helpful comments. Partial financial support was generously provided by Deloitte, Haskins and Sells Foundation. I am solely responsible for all errors and omissions.

1. Introduction

Analysts' forecasts of earnings are increasingly used in accounting and finance research as expectations data, to proxy for the unobservable "market" expectation of a future realization. Since a diverse set of forecasts is available at any time for a given firm's earnings, composites are used to distill the information from the diverse set into a single expectation. This paper considers the relative merits of several composite forecasts as expectations data. One of the primary results is that the most current forecast available outperforms more commonly used aggregations such as the mean or the median. This result is consistent with forecasters incorporating information from others' previous predictions into their own. It also suggests that the forecast date, which previous research has largely ignored, is a characteristic relevant for distinguishing better forecasts.

Researchers have used a variety of methods to aggregate analysts' forecasts into a single expectation. Barefield and Comiskey (1975), and Fried and Givoly (1982) use the mean of a set of forecasts. Brown and Rozeff (1978) use a single forecast from ValueLine. Givoly and Lakonishok (1979) select the "most active" forecaster for each firm from those available in Standard and Poors' Earnings Forecaster. Elton, Gruber, and Gultekin (1981) and Brown, Foster and Noreen (1984) consider both means and medians published in the I/B/E/S Summary database. Brown,

Griffin, Hagerman and Zmijewski (1985) combine a ValueLine forecast with several time-series forecasts. I consider three composites from a set of available forecasts: the mean, the median, and the most current forecast.

The use of predictions from univariate time-series models of earnings as earnings expectations has been more common than the use of analysts' forecasts, in part because of data availability. However, several studies (Brown and Rozeff (1978), Collins and Hopwood (1980), Fried and Givoly (1982)) demonstrate that analysts are more accurate than univariate models, presumably because they can incorporate a broader information set than can a univariate model. Fried and Givoly also find that analysts' forecast errors are more closely associated with excess stock returns than are those of univariate models. An additional limitation of time-series models is their substantial data requirements, which impart a sample selection bias to the research, toward longer-lived and larger firms. Since analysts' forecasts require no parameter estimation, sample selection bias is less severe.

I add to the literature comparing analysts with time-series models by examining two quarterly models as benchmarks for the analysts. My results on the relatively greater accuracy of analysts are consistent with those of previous research. The result that analysts' forecasts more closely reflect the information impounded in stock returns, however, is not replicated here. Adding time-series models has the drawback,

noted above, that the sample size is substantially reduced by their data requirements.[1] However, differences between my results and those reported elsewhere justify the inclusion of time-series models in the paper.

In section 2, I describe several proxies for the analysts' consensus and two quarterly time-series models used in the empirical tests. In section 3 I present the methodology for comparing different forecasts, and in section 4 describe the data. The results are discussed in section 5, and section 6 is a summary with some concluding remarks.

2. Proxies for Expected Earnings

2.1 Defining Consensus for Analysts' Forecasts

The motivations for seeking a consensus expectation when many forecasts are available are primarily practical. First, if individual forecasts contain idiosyncratic error which can be diminished or, ideally, completely diversified away, then more accurate forecasts can be obtained by combining forecasts from different sources into a single consensus number.[2] Second, in many contexts the earnings expectation is not the central issue, but is a necessary piece of data. For example, to control for effects of simultaneous earnings releases in measuring other information events, a measure of unanticipated earnings is

needed. To obtain unanticipated earnings, an accurate earnings expectation is required. If expected earnings are measured with error, as they almost surely are when many heterogeneous forecasts are available, the power of subsequent tests is reduced.

In studies of macroeconomic forecasts, the precision-weighted average has been proposed as the "optimal" combination of forecasts.3 If $\underline{f}$ is a vector of forecasts of a single number from several sources, and if Σ is the variance-covariance matrix of contemporaneous covariances between forecast errors from different sources, then the precision-weighted average f* is defined:

$$f^{*} = \underline{\lambda}' \underline{f} \quad , \tag{2.1}$$

$$\underline{\lambda} = (\Sigma^{-1}\underline{\iota})/(\underline{\iota}'\Sigma^{-1}\underline{\iota}) \quad , \tag{2.2}$$

where $\underline{\iota}$ is a vector of ones, and $\underline{\lambda}$ is the vector of precision-weights applied to forecasts.

The precision-weighted average defined in (2.1) and (2.2) is the optimal combination under quadratic loss if $\underline{f}$ comprises unbiased forecasts for a single series and the precisions are known (Bates and Granger (1969)). The question remains open, however, whether precision-weighted averages are better than alternatives in any empirical sense. Several examples will illustrate this point. First, if quadratic loss is not the correct criterion, then f* is not necessarily optimal. For example, if absolute error is the appropriate loss function, the

precision-weighted average is inferior to the median (see DeGroot (1970) for a proof). Second, if the precisions are unknown and must be estimated, the performance of the precision-weighted average will depend on the data. If, for example, covariances between different sources are not stable over time, then the weights cannot be estimated from existing data. Third, if a cross-section of forecasts is considered, rather than a single series, then the series-by-series precision-weighted averages are inferior under quadratic loss to certain shrinkage estimators, commonly called Bayes-Stein estimators (see James and Stein (1961)).

For analyst forecast data, the second of the above considerations, estimating Σ, is of particular concern. To estimate the covariance between two analysts, a time-series of their predictions for a firm or set of firms is needed. Such consistent time-series are extremely rare in analyst forecast data, since the identities of the individual analysts predicting a given firm's earnings varies considerably from year to year. The unbalanced nature of the data precludes the use of precision-weights on a large sample of firms or analysts.4

I consider the mean forecast, an extreme simplification of the precision-weighted average. The theoretical circumstances under which the mean is an optimal forecast under quadratic loss are fairly restrictive: the forecast errors from different sources must be independent, and the forecasts must be of equal precision. The empirical justification for the extreme

simplification is more compelling. Given the lack of consistent and stable series, weights are likely to be poorly estimated, adding noise to the composite formed from them.

A second definition for the consensus examined here is the median of a set of forecasts. The median is the optimal combination under absolute error loss, and is less sensitive to outliers than the mean and related weighted averages.

An implicit assumption behind the use of either the mean or the median forecast to represent the consensus is that all forecasts are current, so that cross-sectional differences in forecasts are attributable to differential use of the same global set of information. Gains from combining forecasts arise either from the employment of more information in the aggregate than is used by any individual, or from diversification across individuals' idiosyncratic errors.

In fact, however, the analysts' forecasts available at any time vary on how recently they were produced. I refer to this feature as the age of the forecast. If analysts incorporate information from others' forecasts in producing their own, then more current forecasts may be more accurate, and possibly closer to a "market" expectation. I consider the extreme application of this argument, by examining the most current forecast as a definition of consensus.

The motivation for using the most current forecast as a consensus expectation addresses the context in which forecasts are most likely used. The implicit assumption is that, since

information is disseminated relatively rapidly, recent releases have more value than previous ones. The value of an earnings expectation, however, depends upon how it is used by investors and others in decisions. The mechanics by which earnings information is translated into prices or other outcomes are far from well-understood. The most current forecast is used here because it is observable, and is consistent with our understanding of information in capital markets.

2.2 Quarterly Time-series Models of Earnings

I use quarterly time-series models of earnings as benchmarks, against which analysts' forecasts are compared. Analysts have the advantage of a much broader information set than is employed in a univariate model, including industry and firm sales and production figures, general macroeconomic information, and other analysts' forecasts, in addition to the historical series of earnings. Analysts' forecasts, therefore, are likely to be more accurate than forecasts from univariate models.

An advantage of the univariate time-series approach is the relative ease with which earnings data can be obtained for moderate samples of firms. This is tempered by the caveat that the data requirements of the models impart a "survivorship" bias to samples. Another advantage to time-series models is the relative simplicity of the models used to generate expectations.

Parsimonious models with a single, simple ARIMA structure applied to all firms have been shown to predict at least as well as univariate models with more complex, individually-specified structures, when one-step-ahead forecast errors are compared cross-sectionally.5

The primary shortcoming of univariate time-series models as expectations models is their inability to adjust, between earnings announcements, for relevant new information. Models using quarterly data to predict annual earnings represent an improvement over models using only annual data, by allowing revisions of expectations quarterly, instead of only annually (see Hopwood, McKeown, and Newbold (1982)).

A second drawback to the use of time-series models is the underlying assumption of an earnings process which is unchanged over time. Since accounting research frequently examines events which involve changes in reported earnings, representing changes in underlying cash flows, decisions, or the accounting reporting process, this important assumption is frequently violated.

I use the following two quarterly time-series models, from Foster (1977):

$$E[a_{jtq}] = a_{jtq-4} + \theta_{j0} + \theta_{j1}(a_{jtq-1} - a_{jtq-5}) \quad , \qquad (2.3)$$

and:

$$E[a_{jtq}] = a_{jtq-4} + \theta_{j2} \quad , \qquad (2.4)$$

where a_{jtq} denotes quarterly reported earnings for firm j in quarter q of year t, and θ_{j0}, θ_{j1} and θ_{j2} are estimated

parameters. The models are, respectively, a first order autoregressive process in the fourth differences with a drift, and a random walk in the fourth differences with a drift. These models are chosen because of their relative simplicity, and because they have proven to be at least as good as other mechanical quarterly models. The data used and estimation of these models are described in section 4.

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3. Methodology

3.1 Measuring Forecast Errors

Forecast errors are the elementary data I use to evaluate forecasts. The forecast error is defined as the difference between actual earnings per share (EPS)[6] of firm j in year t and the forecast of EPS from source i, at a horizon τ prior to the realization:

$$e_{ijt\tau} = A_{jt} - f_{ijt\tau} \quad . \tag{3.1}$$

The source of the forecast, denoted by i, is one of the following: the mean, the median, or the most current of a set of analysts' forecasts; or one of the two benchmark quarterly models described in section 2.2. The composite analyst forecasts are constructed from a set of forecasts which includes the most recent forecast from each individual in the database, prior to a

fixed horizon date. Forecast selection, the database used, and the forecasting horizon are described in more detail in section 4.

In addition to the raw forecast errors defined in equation (3.1), I present results for two other scales: forecast errors scaled by the average absolute deviation of the past five years' changes in EPS,

$$se_{ijt\tau} = \frac{e_{ijt\tau}}{\frac{1}{5}\sum_{s=t-5}^{t-1} |\Delta A_{js}|} , \qquad (3.2)$$

and forecast errors as a percent of the absolute value of the prior year's EPS,

$$pe_{ijt\tau} = \frac{e_{ijt\tau}}{|A_{jt-1}|} . \qquad (3.3)$$

There are two reasons for considering several scales for forecast errors in this study. The first is comparability with previous work. The second is that EPS forecast errors may be heteroscedastic. That is, there may be differences in predictability of EPS across firms, perhaps related to firm size, earnings variability, or available information.

Equation (3.2) scales forecast errors by the average variation in previous years' EPS, as a benchmark for predictability. The average variation is measured here by the average absolute value of past changes. This measure is less

sensitive to outliers than the standard deviation, and describes the variablility of a random walk with trend when loss is proportional to absolute error.7

Variants of (3.3) have been used frequently in previous research to create a unitless measure (e.g., Cragg and Malkiel (1968), Brown and Rozeff (1978), Beaver, Clarke and Wright (1979), Malkiel and Cragg (1981), and Elton, Gruber and Gultekin (1981)). Equation (3.3) is appropriate if forecasts of EPS growth, not EPS, are relevant for decisions. Alternatively, if predictability is proportional to the level of EPS, then equation (3.3) controls for cross-sectional variation in predictability.

3.2 Aggregating Forecast Errors

If a forecast incorporates all the information available on the forecast date in an unbiased manner, then it can be described as an expectation in the usual statistical sense of the word. Let f** denote such a forecast:

$$f^{**}_{jt\tau} = E[A_{jt} | \Phi_{t\tau}] \quad , \tag{3.4}$$

where $\Phi_{t\tau}$ represents the information available at a horizon τ prior to the realization, and E[|] is the conditional expectation operator.

In the span of time between the forecast date and the realization date, new information may arrive. Even a forecast like (3.4), which may be ideal in the sense of employing all

information available on the forecast date, will omit unanticipated information which arrives later. Forecast errors consist, in part or entirely, of new information revealed over the forecast horizon, i.e. between forecast and realization.

There are two closely-related implications of new information being impounded in forecast errors. First, contemporaneous forecast errors will not, in general, be cross-sectionally independent observations. Second, forecast errors within a year which are aggregated cross-sectionally may appear to be "biased" because of the common new information reflected in them.

Events such as unanticipated macroeconomic shocks may affect many firms in a similar manner, inducing a correlation in forecast errors for different firms for the same year and horizon. Moreover, since different forecast horizons within a year overlap, errors are correlated across horizons within a year, in general.

If forecast errors are positively correlated across firms within years, then statistical comparisons based on data from a short time-series which assume that observations are cross-sectionally independent will overstate the statistical validity of the results. Several studies (Brown and Rozeff (1978), Elton, Gruber and Gultekin (1981), Malkiel and Cragg (1980), for example) have compared forecasts using criteria such as the number or proportion of times that one forecasting method outpredicts another. This criterion, or any other which assumes

independent observations and is applied to a cross-section, could obtain the appearance of statistically significant superiority in forecasting ability from an anecdotal difference.

Forecast bias, or the appearance of bias, is similarly affected by common information reflected in a cross-section of forecast errors. The forecast defined in (3.4) is unbiased if the expectation of its error, e^{**}, conditional on information available at the forecast date, is zero:

$$E[e^{**}_{jit} | \Phi_{it}] = 0 \tag{3.5}$$

Because of changes in the information available between the forecast and realization dates, cross-sectional aggregations of forecast errors from unbiased forecasts may display non-zero means, reflecting common effects of unanticipated events. This is not correctly interpreted as bias, but rather as time-period-specific new information.

An analogous explanation, based on effects of common unanticipated information, does not apply to firm-specific effects measured across years. If a forecast fully impounds information from previous mistakes in an unbiased manner, then systematically recurring events will not remain unanticipated year after year. Thus recurrent firm-specific forecast errors are not expected to arise on the basis of information that was unavailable at the time the forecast was made.

3.3 Evaluating Forecasts - Bias

A simple model of time-period effects in forecast errors is:[9]

$$e_{jt\tau} = \mu_{t\tau} + \eta_{jt\tau} \quad , \qquad (3.6)$$

where $\mu_{t\tau}$ is the average forecast error for year t and horizon τ, and $\eta_{jt\tau}$ is a random error term, representing the deviation of firm j's forecast error from the common annual mean.

I estimate (3.6) using least squares with a dummy variable for each year.[10] The test for bias is based on the grand mean of the estimated annual averages:

$$\bar{\mu}_{\tau} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{t\tau} \quad , \qquad (3.7)$$

where T is the number of years in the sample, and the $\hat{\mu}_{t\tau}$ are the year-specific average forecast errors, estimated separately for each horizon τ. The average $\bar{\mu}_{\tau}$ defined in (3.7) is a linear combination of least-squares coefficients, with estimated standard error:

$$s_{\bar{\mu}_{\tau}} = \frac{s_{\eta}}{T} \cdot [\underline{\iota}'(X'X)^{-1}\underline{\iota}]^{1/2} \qquad (3.8)$$

where $\underline{\iota}$ is a vector of ones of length T, X is the matrix of dummy variables, and s_{η} is the regression residual standard error. For the model given by equation (3.6), equation (3.8) reduces to:

$$s_{\bar{\mu}_{\tau}} = \frac{s_{\eta}}{T} \cdot [\sum_{t=1}^{T} \frac{1}{J_t}]^{1/2} \qquad (3.9)$$

where J_t is the number of observations in year t. The standard error for the bias test is a weighted version of the residual standard error s_η, constructed from the $\eta_{jt\tau}$. The residuals $\eta_{jt\tau}$ are deviations from the annual averages, and so are purged of this time-period-specific information which induces cross-sectional correlation in the $e_{jt\tau}$. The precision contributed by each annual average $\hat{\mu}_{t\tau}$ to the precision of the mean $\bar{\mu}_\tau$ is determined by the overall standard error, s_η, and the number of observations, J_t, in that year.

The ratio of (3.7) to (3.9) is evaluated as a t-statistic, and is used to measure forecast bias for each analyst composite, mean, median and most current, and for the quarterly models.

3.4 Evaluating Forecasts - Accuracy

I use an approach similar to the bias evaluation described in the previous section for evaluating relative forecast accuracy. Accuracy is defined as absolute or squared forecast error. The model is:

$$|e_{jt\tau}| = \delta_{1j\tau} + \delta_{2t\tau} + \xi_{jt\tau} \qquad , \qquad (3.10)$$

or:

$$e^2_{jt\tau} = \gamma_{1j\tau} + \gamma_{2t\tau} + \zeta_{jt\tau} \qquad , \qquad (3.11)$$

where the $\delta_{1j\tau}$ and the $\gamma_{1j\tau}$ measure average accuracy for each

firm j, and the $\delta_{2t\tau}$ and $\gamma_{2t\tau}$ measure average accuracy for each year t. The $\xi_{jt\tau}$ and the $\zeta_{jt\tau}$ are deviations from the average accuracy in this sample for firm j and for year t. Differences in accuracy across firms could arise, for example, if there are persistent differences in the amount of information available for different firms. Differences in accuracy across years could arise if there are more, or larger, unanticipated events in some years than in others.

Equations (3.10) and (3.11) are estimated using least squares on a set of dummy variables for firms and years. Average accuracy is computed in a manner analogous to equation (3.6), as a linear combination of the estimated effects:[11]

$$\bar{\delta}_{\tau} = \frac{1}{J} \sum_{j=1}^{J} \hat{\delta}_{1j\tau} + \frac{1}{T} \sum_{t=1}^{T} \hat{\delta}_{2j\tau} \quad , \qquad (3.12)$$

or:

$$\bar{\gamma}_{\tau} = \frac{1}{J} \sum_{j=1}^{J} \hat{\gamma}_{1j\tau} + \frac{1}{T} \sum_{t=1}^{T} \hat{\gamma}_{2j\tau} \quad , \qquad (3.13)$$

Equation (3.12) gives the average absolute error accuracy, and (3.13) gives the average squared error accuracy. The average accuracies in equations (3.12) and (3.13) have standard errors which are estimated, respectively as:

$$s_{\bar{\delta}_{\tau}} = s_{\xi} \cdot [\underline{\omega}'(Z'Z)^{-1}\underline{\omega}]^{1/2} \quad , \qquad (3.14)$$

and:

$$s_{\bar{\gamma}_{\tau}} = s_{\zeta} \cdot [\underline{\omega}'(Z'Z)^{-1}\underline{\omega}]^{1/2} \quad . \qquad (3.15)$$

In (3.14) and (3.15), Z represents the matrix of dummy variables used to estimate equations (3.10) and (3.11), $\underline{\omega}$ is the vector of weights that transform the estimated parameters into the averages defined in (3.12) and (3.13), and s_ξ and s_ζ are the residual standard errors from the regression equations.

The estimates in equations (3.12) through (3.15) are computed for the mean, median and most current analyst forecasts, and for the forecasts from the quarterly models. Pairwise differences in accuracy are compared across forecast sources using a t-statistic constructed from the average accuracies from (3.12) or (3.13) and their standard errors from (3.14) and (3.15).

3.5 Evaluating Forecasts - Market Association

The criteria developed in the previous two sections, bias and relative accuracy, are objective and reasonably common in evaluation of forecasts. They do not, however, address the context in which the forecasts are used. Both researchers' and investors' use of forecast data in contexts related to securities markets suggests that association with stock returns may provide a relevant empirical comparison.

In section 3.2 I argued that forecast errors will impound information arriving after the forecast date. Subject to the qualifications discussed below, this implies that the forecast

error will be positively correlated with new information impounded in stock returns over the forecast horizon.

I measure the new information impounded in stock returns by the cumulated excess returns from a market model. The excess return is the deviation of the observed return R_{js} from its expectation based on the model:

$$E[\ln(1 + R_{js})] = \alpha_j + \beta_j \ln(1 + R_{Ms}) \qquad (3.16)$$

where R_{Ms} is the return on a market portfolio of securities. The data and estimation of parameters in equation (3.16) are discussed in section 4.

Excess returns, not raw stock returns, are used since excess returns represent unanticipated returns. Informationally efficient forecasts will have forecast errors comprising only unanticipated information. Forecasts which are not informationally efficient will have forecast errors consisting of both unanticipated information and information which was available at the forecast date but was not incorporated into the forecast. Forecast errors from inefficient forecasts may therefore be correlated with the anticipated component of stock returns. This correlation could cause a stronger association with raw returns to be observed for inefficient forecasts than for efficient forecasts. This argues against using the association between raw returns and forecast errors as a criterion for evaluating forecasts, and in favor of using only the unanticipated portion of returns.

Two qualifications to the implied association between the

information reflected in excess stock returns and that reflected in earnings forecast errors are worth noting. First, the information relevant to valuing the firm's common stock is not precisely the same as the information relevant to current-year earnings. There are errors in both variables with respect to the measured association between them which represents the common information. Non-recurring events, whether they are treated as extraordinary items or not, may affect earnings in one particular year, but may be inconsequential to the long-term value of the firm. Conversely, events that influence longer-term prospects, such as changes in investment opportunities, may affect the value of the firm without altering current earnings.

Second, excess returns are constructed to exclude one source of unanticipated information. The excess return is purged of its systematic relation with market returns, which includes both anticipated and the unanticipated components. Elimination of the anticipated component is desirable, as discussed above. Elimination of the unanticipated portion, however, will reduce the measurable association between excess returns and forecast errors. Correction of this problem requires a model of the expected return on the market, so that the unexpected component can be isolated. However, while the power of the tests for positive association is reduced, the reduction in power does not vary across forecast sources. It will not affect the *relative* degree of association across sources.

Both qualifications noted above will have the effect of

reducing the measurable association between forecast errors and excess returns. Nevertheless, previous studies facing the same inherent difficulties have found statistically significant positive associations between unexpected earnings and excess stock returns (Ball and Brown (1968), Beaver, Clarke and Wright (1979), and Fried and Givoly (1982), for example).

The regression model used to estimate the association between cumulated excess returns, represented by $U_{jt\tau}$, and forecast errors, $e_{ijt\tau}$, is:

$$e_{ijt\tau} = \alpha_{1ij\tau} + \alpha_{2it\tau} + \beta_{i\tau} U_{jt\tau} + v_{ijt\tau} \qquad (3.17)$$

In (3.17), $\beta_{i\tau}U_{jt\tau}$ is the portion of the forecast error from source i at horizon τ which is systematically related to excess returns. The slope coefficient $\beta_{i\tau}$ is the covariance between excess returns and forecast errors, adjusted for firm and year effects, in units of the variance of excess returns. Using excess returns as the independent variable and forecast errors as dependent has the desirable feature that $\beta_{i\tau}$ and its associated t-statistic have the same scale for all sources i. If the roles of these two variables were reversed in the regression equation, the estimated regression slope coefficient would depend explicitly on the forecast error variance from source i.

The constants $\alpha_{1ij\tau}$ and $\alpha_{2it\tau}$ measure, respectively, firm- and year-specific average forecast errors, conditional on the systematic relation with excess returns. The $\alpha_{2it\tau}$, the year effects, play an important role in equation (3.17), since they capture the time-period-specific information in forecast errors

which is not captured by excess returns.[12] Among other things, they include the average effect of omitting the unanticipated component of the market return. If the $\alpha_{2it\tau}$ are not included in the model, then they are impounded in the regression residuals as an omitted variable. This induces cross-sectional correlation in the residuals, which if ignored leads to incorrect statistical inferences, as was discussed above for the bias computation.[13]

Equation (3.17) is estimated by stacking the regressions for the five forecast sources, and estimating them jointly. The forecast sources are the mean, median and most current analyst forecast and the two quarterly models. Estimations are performed jointly for the five forecast sources, and separately for each forecast horizon.

Since the matrix of independent variables, consisting of cumulated excess returns over the forecast horizon and dummy variables indicating firms and years, is the same for each of the forecast sources, there is no efficiency gain over equation-by-equation least squares (see Zellner (1962)). The advantage of stacking the equations is for joint estimation of the firm and year effects, so that observations from each of the five forecast sources are adjusted for the same firm and year effects.

A further advantage of stacking the equations is that statistical testing is simplified, since a set of linear constraints on the estimated slope coefficients $\beta_{i\tau}$ generates direct tests of differences in slope across forecast sources. For example, if $\underline{\beta}_{\tau}$ is the vector of five slope coefficients, one

for each forecast source, and if $\underline{c}_{12}'$ is the vector (1,-1,0,0,0), then $\underline{c}_{12}'\underline{\beta}_\tau$ estimates the difference in slopes between the first and second sources, with standard error:

$$s_{\underline{c}'\underline{\beta}} = s_v \cdot [\underline{c}'(X'X)^{-1}_{\beta}\underline{c}]^{1/2} \tag{3.18}$$

In (3.18), s_v is the residual standard error from the joint estimation of equation (3.17). $(X'X)^{-1}{}_{\bar{\beta}}$ is the lower-right submatrix of five rows and five columns from the $(X'X)^{-1}$ matrix of equation (3.17). This submatrix determines the variance-covariance relations among the five slope coefficients.

Linear constraints of the form of $\underline{c}_{12}$ are used to evaluate differences in the slope coefficients, i.e. differences in the association between excess returns and forecast errors, across forecast sources. The results from estimation of equation (3.17) are in Tables 8 through 11, and are discussed in section 5.

4. Data Description

The forecast data are from the Institutional Brokers Estimate System, or I/B/E/S, a database developed by the Lynch, Jones and Ryan brokerage house. The database consists of estimates from between 50 and 130 brokerage houses, each employing many analysts. EPS are forecast for between 1000 and 2500 firms, depending on the month and year in question. From each brokerage house, at most one analyst is reported predicting EPS for any given firm. The data used in this paper are

individual analysts' forecasts, compiled from July 1975 through September 1982.[14]

The database is updated on or around the 25th of each month. From the updated list of forecasts, summary statistics such as the mean, the median, the standard deviation, the number increasing, etc., are computed. The summary statistics are then sold to clients, primarily institutional investors.

COMPUSTAT is the source of earnings data and most earnings announcement dates. The remaining announcement dates are from the Wall Street Journal (WSJ) and its Index. Stock return data and the trading day calendar are from the CRSP Daily Returns file. Data on stock splits and stock dividends are from the CRSP Monthly Master file.

The initial sample comprises the set of firms in the I/B/E/S database with December yearends, and with forecasts available for each year from 1975 through 1981. This set contains 508 firms, and 3556 firm-years. Firm-years are excluded if the annual earnings are not available on COMPUSTAT, or if all four quarterly earnings announcement dates are not available from COMPUSTAT or the WSJ. This reduces the sample to 457 firms, with 3440 firm-years. The estimation requirements of the quarterly models, 30 continuous quarters of data prior to 1975-IV, further reduce the sample to 190 firms, with 1284 firm-years. The final requirement, listing on CRSP, reduces the sample to 184 firms with 1260 firm-years.

Analysts occasionally produce forecasts for fully-diluted,

rather than primary, EPS. Primary EPS are earnings divided by the average number of outstanding common shares, including common stock equivalents such as stock options and warrants. Fully-diluted EPS are earnings divided by the average number of outstanding common shares, computed "to show the maximum potential dilution of current EPS" (APB Opinion No. 15), including in the denomimator such things as contingently issuable common stock. Forecasts of fully-diluted EPS are converted to primary, using the ratio of fully-diluted to primary EPS for that firm and year from COMPUSTAT. Forecasts are also adjusted for changes in capitalization which are announced between the forecast date and the annual earnings announcement date.

Forecasts for each firm and year are selected at five fixed horizons of less than one year in duration. They are: 240, 180, 120, 60 and 5 trading days prior to the announcement of annual earnings. The first four horizons correspond roughly to dates following each of the year's quarterly earnings announcements; the fifth is immediately prior to the annual announcement. For example, a horizon of 240 trading days will usually correspond to a date after the previous year's annual announcement, and before the current year's first quarter announcement. A horizon of 180 trading days will typically correspond to a date between the first quarter announcement and the second quarter announcement; and so on.

The motivation for selecting horizons corresponding to dates in different fiscal quarters is, first, to observe whether there

is an evolution of expectations over the course of the year, and second, to ensure that the horizons differ in a well-defined, observable, and potentially relevant respect: the amount of quarterly earnings data available.15

Given a horizon τ, firm j, and year t, the selected forecasts are the most recent available from each brokerage house issuing a forecast for firm j in year t. I use the dates assigned to forecasts by analysts, not the dates of the I/B/E/S file in which they first appear. The lag between the analyst's date for a forecast and the date of its first appearance on I/B/E/S averages 34 trading days, and has a standard deviation of 44.5 trading days. Thus, some recently-updated forecasts are omitted from each monthly listing by I/B/E/S. Since published summary statistics are computed from these monthly lists, the summary statistics also fail to reflect some recent updates.

Using analysts' dates instead of I/B/E/S "publication" dates results in a realignment of the data, with fewer omissions of recently updated forecasts. Previous studies of analysts' forecasts have used the publication date, not the analyst's forecast date, to select forecasts. For example, Fried and Givoly (1982) and Givoly and Lakonishok (1982) select their samples based on the publication date of the Standard & Poors' Earnings Forecaster, their source of forecast data. Fried & Givoly go on to use analysts' dates within that sample to distinguish new and old forecasts. Brown and Rozeff (1978) and Brown, Foster and Noreen (1984) use datasets for which individual

analysts' forecast dates are not available. Using publication dates instead of forecast dates probably biases results against analysts, by failing to include some recent updates of forecasts.

Once the set of available forecasts is selected for each firm j, year t and horizon τ, I find the mean, the median, and the most current of this set to proxy for the consensus.

The quarterly models (2.3) and (2.4) are estimated for each firm, for each quarter from 1975-I through 1981-IV. Parameter estimates are updated each quarter, using the previous thirty quarters' observations. Observations are adjusted for changes in the number of outstanding shares. Annual forecasts are constructed from quarterly forecasts by summing the appropriate realizations and forecasts. For example, in quarter 3, there have been two realizations of quarterly earnings for the year, and two quarters remain to be forecast. The annual forecast from a quarterly model for quarter 3 is the sum of actual earnings for quarters 1 and 2, and forecasts for quarters 3 and 4.

Because of a small number of untraceable influential observations which altered the regression results, I imposed an arbitrary censoring rule on the data as well: all forecast errors larger than \$10.00 per share in absolute value were deleted from the sample. Since typical values for EPS numbers are in the range of \$1.00 to \$5.00 per share, errors of sufficient magnitude to be deleted are rare, and suggest a data entry or transcription error. This censoring rule does not eliminate all observations which appear as outliers on data

plots, since the error transformations described in equations (3.2) and (3.3) can have denominators close to zero.

Excess returns are estimated from a daily market model in logarithmic form:

$$\ln(1 - R_{js}) = \alpha_j + \beta_j \ln(1 + R_{Ms}) + \varepsilon_{js} \qquad (4.1)$$

where R_{js} is the return to security j on day s, R_{Ms} is the return on the CRSP equally-weighted market portfolio of securities on day s, and ln denotes the natural logarithm transformation.[16]

The parameters of (3.14) are estimated for each firm in the study using 200 trading days of data at a time, beginning in July 1974. Estimated parameters are used to predict ahead 100 trading days, and excess returns are the difference between the realization $\ln(1 + R_{js})$ and the prediction based on (3.14). After each iteration of estimation and prediction, the estimation period is rolled forward by 100 trading days, and new parameters are estimated.

The estimation procedure produces a stream of daily excess returns, ε_{js}. The ε_{js} are cumulated over each forecast horizon, from the horizon date through the announcement date of annual EPS, to form $U_{jt\tau}$, the measure of new information arriving over horizon τ in year t for firm j.

5. Results

The fundamental difference between the most current analyst

forecast as a consensus definition and either the mean or the median, is that the former is constructed using the forecast date, while the latter two are not. In Table 1, the distributions of forecast ages are compared for the three alternative definitions of analyst consensus. The age of a forecast is defined to be the difference, measured in trading days, between the forecast date and the horizon date chosen for this study. More generally, it can be considered the lag between the forecast date and an event date of interest to the researcher.

For each firm, year, and horizon, the consensus forecasts are computed from the set of available analysts' forecasts. The set of available forecasts contains the last forecast from each analyst, produced prior to the horizon date. In Table 1, the ages of the mean and median forecasts are defined to be, respectively, the mean and the median of the ages of the forecasts in the set of available forecasts for each firm, year and horizon. The distribution described in Table 1 is over all firms and years, for each horizon.

As expected from its definition, the most current forecast has a distribution of ages much closer to zero than either the mean or median. For the four longer horizons (240, 180, 120, and 60 trading days), over fifty percent of the most current forecasts are less than five trading days old. By contrast, over fifty percent of the mean or median ages at all horizons are more than forty trading days. While some of these older forecasts may

represent circumstances where little new information has arrived, so there was no need to update, the accuracy results which follow suggest that this is not always the case.

In Table 2, the bias results are presented. The reported numbers are the forecast bias, computed as in equation (3.7), and a t-statistic to test the null hypothesis of no bias. Results are given for three different definitions of the forecast error, and the results vary considerably across definitions.

Generally, the unscaled forecast error (equation (3.1)) and the forecast error scaled by average absolute EPS changes (equation (3.2)), in Panels A and B, exhibit statistically significant negative bias. The forecast error measured as a percent of prior EPS, in Panel C, exhibits mixed results, mostly positive or zero. Of the three analyst consensus measures, the median uniformly exhibits the smallest bias, usually indistinguishable from zero.

Negative bias corresponds to overestimates of EPS. Negative bias in analysts' forecasts is consistent with some conventional wisdom, which says that analysts prefer to make optimistic predictions and "buy" recommendations, to maintain good relations with management.[17] The evidence is weak, however, in two respects. First, the negative bias result is very sensitive to the definition of forecast errors. The median analyst forecast appears to be unbiased under all transformations of the forecast error. The percent transformation, reported in Panel C, gives mixed results which would not lead to a general conclusion of

negative bias. Second, in Panels A and B, when the estimates from analysts are significantly negative, they are statistically indistinguishable from those from mechanical time-series models. The motive of maintaining good relations with management cannot be ascribed to these models. Support for the contention that analysts preferentially issue optimistic forecasts is at best weak.

An alternative explanation which is also consistent with these results is that analysts issue unbiased forecasts, but this seven-year period, 1975 through 1981, is one with primarily negative unanticipated EPS. Unfortunately, the way to distinguish between the hypothesis of deliberate optimistic bias and this alternative is to collect data for a longer span of years.

Tables 3 through 7 summarize the results on forecast accuracy. The average absolute error, computed as described in equation (3.12) for each forecast source, appears in Table 3. Average squared errors, from equation (3.13), are in Table 4. Table 5 contains t-statistics testing pairwise differences in accuracy among analysts. Tables 6 and 7 contain t-statistics testing pairwise differences in accuracy between analysts and the quarterly models.

Both Table 3 and Table 4 display a consistent pattern of increasing forecast accuracy as the earnings announcement date approaches, for all forecast sources. That is, average absolute and squared error decline uniformly as the year progresses, for

analysts and for quarterly models. This is consistent with forecasts incorporating some new information relevant to the prediction of EPS over the course of the year.

In Tables 3 and 4 it appears that the most current analyst is no worse than the other sources, and that analysts dominate quarterly models in the longer horizons. The reader of Tables 3 and 4 should avoid using the heuristic test of counting the number of times that the most current forecaster is most accurate to assess these differences. The relative performance results are highly correlated, both across horizons and across definitions of the forecast error. The results of a statistical test for the differences in accuracy which are suggested by a perusal of Tables 3 and 4 appear in Tables 5 through 7.

In Tables 5 through 7, a positive difference means that the first of the pair is less accurate. Table 5 contains the results of pairwise comparisons among the three analyst consensus definitions. In terms of absolute error, which is reported in Panel A, when the differences are significant they favor the mean over the median and the most current forecaster over either the mean or the median. In Panel B, where differences in squared error accuracy are presented, there are no measurable differences in accuracy among the three analyst consensus definitions.

The results reported in Tables 6 and 7 indicate that analyst forecasts generally dominate the time-series models at the longer horizons. For the 240, 180 and 120-trading-day horizons, wherever differences are statistically significant, the results

favor analysts over the quarterly models. This evidence is consistent with analysts using a broader information set than can be exploited by a univariate model.

At the 60-trading-day horizon, however, the quarterly time-series models dominate the mean and the median analyst forecast in all comparisons where significant differences exist. The most current forecast is never dominated to a statistically significant extent by the quarterly models, but generally is indistinguishable from them.

The accuracy results reported in Tables 3 through 7 are mixed. Often, differences in accuracy between forecast sources are statistically insignificant. Where they are statistically significant, however, the results generally conform with expectations. The most current forecaster is at least as good as, and by some measurements dominates, the mean or median. This is consistent with the most current forecast impounding information from previously released forecasts. The results reported in here probably understate the difference between the most current forecast and the mean and median definitions which appear in most other published work. The sample used here was selected to eliminate the "publication lag" which is characteristic of datasets which use publication dates, rather than analysts' dates, to select forecasts.

Analysts are generally at least as good as, and in longer time horizons dominate, univariate time-series models. This is consistent with analysts incorporating a broader information set

into their forecasts than simply the univariate time-series. Again, the results here may understate differences. Since the sample of firms is reduced sharply by the data requirements of the time-series models, the selection process may exclude firms where analysts' information advantage is largest.

Tables 8 through 11 contain the results from estimation of model (3.17), to test for positive association between forecast errors and excess returns. The method used is to regress the forecast error, or one of the transformations of the forecast error, on the cumulative excess returns over the forecast horizon, and to test for a significant positive slope.[18] Table 8 contains adjusted R^2 and the F-statistic on the full model, for each forecast horizon, along with information on sample sizes and number of estimated parameters. Table 9 contains incremental F-tests for parts of the model separately. In Table 10, the estimated slope coefficients and their associated t-statistics are reported, and in Table 11 the tests for differences in the estimated slope coefficients across forecast sources are reported.

According to results reported in Table 8, equation (3.17) explains between 9% and 16% of the variation in forecast errors, with slight variations across horizons and across definitions of the dependent variable. The largest adjusted R^2 appears at the 5-trading-day horizon, though differences in explanatory power of model (3.17) across horizons are slight. The weakest results occur when the percent transformation of forecast errors is the

dependent variable, but again differences are not large across transformations of the error. All variants of the model have statistically significant explanatory power, according to the regression F-statistics.

The incremental F-statistics in Table 9 confirm that the year-specific effects are important in equation (3.17). The F-statistic on the year-specific effects tests the null hypothesis:

$$H_0 : \alpha_{2i1\tau} = \alpha_{2i2\tau} = \ldots = \alpha_{2iT\tau} = 0 \qquad (5.1)$$

That is, the F-statistic tests the null hypothesis that estimation of year-specific intercepts adds no explanatory power to the model. This hypothesis is rejected at the .05 level at all horizons, and at the .001 level or better at the horizons longer than 5 days. The importance of year effects in the model increases with the length of the horizon. This is consistent with the information-based explanation for their inclusion in the model, namely that forecast errors impound time-period-specific unanticipated information. Over longer horizons, loosely speaking, the "quantity" of unanticipated information is greater. The strength of this result also confirms the assertions made earlier that a cross-section of forecast errors for a single time period is not a set of independent observations.

The F-statistics on firm-specific effects reported in Table 9 also reject the null hypothesis, which is:

$$H_0 : \alpha_{1i1\tau} = \alpha_{1i2\tau} = \ldots = \alpha_{1ij\tau} = 0 \qquad (5.2)$$

There are measureable firm-specific differences in average

forecast error at all horizons, even after the adjustment for firm-specific information impounded in excess returns. The strength of this result varies little across forecast horizons and across transformations of the dependent variable.

The importance of the slope coefficients in model (3.17), indicated by the F-statisic reported in Table 9, varies across forecast horizons and across transformations of the dependent variable. The individual slope coefficients reported in Table 10, however, are of greater relevance. Generally, the results in Table 10 show a pattern of positive association between forecast errors and excess returns. A positive association is expected if: (1) there is some overlap between information relevant to firm value and information relevant to current-year earnings, and (2) some of this overlapping information is unanticipated both by investors and by the predictor of EPS.

The statistical significance of the positive association varies with the definition of the dependent variable, and with the forecast horizon. The strongest results are found for the unscaled forecast error, and for the 120-day horizon. Among the analyst consensus forecasts, the strongest results are generally for the most current forecaster, which is consistent with the most current forecaster acting as a reasonable composite of analysts' information. The strongest results, and the only ones which are consistently positive and statistically significant, however, are for the quarterly autoregressive model, equation (2.3). This pattern of relative performance does not vary

substantially across horizons or across transformations of the dependent variable. This result is anomalous, especially in light of the quarterly model's relative inaccuracy. It indicates that forecast errors from a quarterly autoregressive model are more highly correlated with excess returns than are forecast errors from analysts forecasts.

Table 11 contains the results of statistical tests for the differences in association observed in Table 10. Results are shown for tests of pairwise differences between the quarterly autoregressive model and all other forecast sources, and for differences between the most current analyst and the mean and median analyst forecasts. The statistical tests confirm the anomalous result, that errors from a mechanical quarterly model often are significantly more closely related to excess returns than errors from analysts. In addition, the tests indicate that while the most current forecast typically shows the strongest result among analyst consensus forecasts, the difference is not statistically significant, in general.

6. Summary and Conclusions

Analysts' predictions of EPS are a potential source of "market expectations" information. I have examined properties of different composites, or consensus forecasts. Results reported here indicate that the most current forecast from a set of

analysts' forecasts is a reasonable aggregation of the information in the set.

Five alternate sources of forecasts are examined: the mean, median, and most current from a set of analysts' forecasts, an autoregressive model in fourth differences of the univariate series of quarterly EPS, and a fourth-differenced random walk using quarterly EPS. The two quarterly time-series models are included primarily as benchmarks.

The most current forecast is at least as accurate as either the mean or median forecast, and generally dominates them in absolute error terms. This result indicates that the date of the forecast is relevant for determining its accuracy, and dominates "diversification" obtained by aggregating forecasts from different sources. Since most published aggregations of forecasts and most previous research treat all forecasts as if they are equally current, they ignore this relevant piece of information. In this sample the forecast error from the most current forecast is more closely associated with excess returns over the forecast horizon than the error from the mean or the median forecast, but the difference in association is not, in general, statistically significant.

Analysts generally are significantly more accurate than time-series models. Errors from the quarterly autoregressive model, however, appear to be more closely related with excess returns over the forecasting horizon than those of analysts, however. Because of this anomalous result, it is unclear that

analysts provide a better model of the "market expectation" than mechanical models.

It should be noted, though, that the sample of firms was reduced sharply by the data requirements of the time-series models. This sample, with its selection bias toward longer-lived firms with continuous data available, does not clearly isolate cases where analysts might be expected to have most advantage over mechanical models, and perhaps eliminated many of these cases. These firms, where there is a substantial amount of non-earnings information expected to have an impact on earnings, may be a fruitful area for future investigation.

Table 1

Selected Characteristics of the Distribution of Forecast Ages,[1] for the Mean, Median and Most Current Analyst Forecasts,[2] for Five Forecast Horizons[3]

		Fractiles					Sample Moments			
Source	Horizon	.1	.25	.5	.75	.9	mean	stdev	skew	N
mean	240	34	46	60	74	89	61.5	24.7	0.8	1198
	180	33	43	58	73	91	59.9	23.9	0.8	1235
	120	34	47	62	82	102	65.9	28.1	1.0	1254
	60	38	51	67	88	110	71.7	31.8	1.6	1258
	5	40	52	67	87	109	72.3	31.2	2.5	1260
median	240	7	20	51	83	127	59.4	47.9	1.1	1198
	180	5	16	41	78	131	56.6	54.5	1.5	1234
	120	7	19	47	80	135	61.1	58.0	1.8	1254
	60	7	19	49	88	155	66.6	67.7	2.0	1258
	5	15	26	43	71	131	61.7	60.8	2.6	1260
current	240	1	2	4	14	43	14.4	24.7	3.3	1198
	180	1	1	3	9	24	9.0	16.9	4.8	1233
	120	1	2	4	11	25	10.0	18.8	6.3	1254
	60	1	1	4	10	26	10.6	22.5	6.8	1259
	5	1	5	11	20	34	15.8	22.0	8.9	1259

Notes:

[1]The age of a forecast is the number of trading days between the analyst's forecast date and the horizon date chosen in this study. For the consensus sources, age is defined:
- mean - the mean of the ages of available analyst forecasts.
- median - the median of the ages of available analyst forecasts.
- current - the age of the most recent analyst's forecast.

[2]The forecast sources are:
- mean - the mean of available analysts' forecasts.
- median - the median of available analysts' forecasts.
- current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 2

Forecast Bias,[1]

for Five Forecast Sources,[2] at Five Forecast Horizons[3]

(t-statistics[4] are in parentheses)

	Horizon: Source:	240	180	120	60	5
Panel A: Unscaled error [Equation (3.1)]	q.a.r.	-0.15	-0.11	-0.14	-0.08	
		(-3.82)	(-3.15)	(-5.18)	(-4.11)	
	q.r.w.	-0.09	-0.05	-0.11	-0.06	
		(-2.17)	(-1.49)	(-4.24)	(-3.25)	
	mean	-0.08	-0.12	-0.12	-0.09	-0.05
		(-2.09)	(-3.57)	(-4.70)	(-4.96)	(-2.74)
	median	-0.03	-0.05	-0.06	-0.02	0.02
		(-0.72)	(-1.52)	(-2.25)	(-1.19)	(1.00)
	current	-0.08	-0.10	-0.09	-0.04	-0.02
		(-1.91)	(-2.93)	(-3.27)	(-2.34)	(-1.42)
Panel B: Scaled error [Equation (3.2)]	q.a.r.	-0.24	-0.12	-0.20	-0.11	
		(-3.69)	(-2.41)	(-4.70)	(-3.59)	
	q.r.w.	-0.14	-0.03	-0.15	-0.08	
		(-2.24)	(-0.66)	(-3.57)	(-2.56)	
	mean	-0.17	-0.20	-0.18	-0.14	-0.07
		(-2.58)	(-4.05)	(-4.20)	(-4.35)	(-2.08)
	median	-0.09	-0.09	-0.08	-0.03	0.03
		(-1.38)	(-1.89)	(-1.83)	(-0.94)	(1.00)
	current	-0.18	-0.17	-0.13	-0.08	-0.04
		(-2.84)	(-3.48)	(-3.01)	(-2.60)	(-1.36)

Table 2 (Continued)

	Horizon: Source:	240	180	120	60	5
Panel C: % error [Equation (3.3)]	q.a.r.	0.05 (1.90)	0.05 (2.14)	.00 (-0.31)	-0.01 (-0.69)	
	q.r.w.	0.06 (2.24)	0.07 (3.25)	0.03 (1.78)	0.01 (1.54)	
	mean	-0.01 (-0.52)	-0.02 (-0.80)	-0.02 (-1.61)	-0.02 (-2.72)	-0.02 (-2.55)
	median	.00 (0.07)	.00 (0.05)	-0.01 (-0.37)	-0.01 (-0.70)	.00 (0.21)
	current	-0.01 (-0.34)	-0.01 (-0.47)	-0.01 (-0.94)	-0.01 (-1.31)	-0.01 (-1.11)

Notes:

[1]The computation of forecast bias and its associated t-statistic are described in equations (3.6) through (3.9) in the text.

[2]The forecast sources are:

q.a.r. - a quarterly autoregressive model in fourth differences; equation (2.3) in the text.

q.r.w. - a random walk model with drift in fourth differences; equation (2.4) in the text.

mean - the mean of the available analysts' forecasts.

median - the median of the available analysts' forecasts.

current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

[4]The degrees of freedom for all reported t-statistics are over 1,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points of the N(0,1) distribution are 1.96 and 2.58, respectively.

Table 3

Forecast Accuracy:
Average Absolute Forecast Error[1]
for Five Forecast Sources,[2] and Five Forecast Horizons[3]

Dependent Variable:	Horizon: / Source:	240	180	120	60	5
Unscaled error [Equation (3.1)]	q.a.r.	0.975	0.780	0.592	0.350	
	q.r.w.	0.963	0.781	0.620	0.363	
	mean	0.747	0.645	0.516	0.395	0.291
	median	0.788	0.677	0.546	0.435	0.321
	current	0.742	0.610	0.468	0.342	0.292
Scaled error [Equation (3.2)]	q.a.r.	1.478	1.112	0.867	0.505	
	q.r.w.	1.494	1.121	0.919	0.523	
	mean	1.147	0.990	0.777	0.616	0.467
	median	1.208	1.035	0.833	0.677	0.516
	current	1.181	0.958	0.733	0.555	0.492
% error [Equation (3.3)]	q.a.r.	0.337	0.273	0.191	0.115	
	q.r.w.	0.335	0.273	0.212	0.124	
	mean	0.244	0.212	0.164	0.121	0.090
	median	0.255	0.219	0.173	0.132	0.096
	current	0.242	0.202	0.154	0.104	0.088

Notes:

[1]The computation of average absolute error is described in equations (3.10) and (3.12) in the text.

[2]The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (2.3) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2.4) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 4

Forecast Accuracy:
Average Squared Forecast Error[1]
for Five Forecast Sources,[2] and Five Forecast Horizons[3]

Dependent Variable:	Horizon: / Source:	240	180	120	60	5
	q.a.r.	2.771	1.877	1.203	0.460	
Unscaled	q.r.w.	2.626	1.897	1.255	0.447	
error	mean	1.531	1.239	0.818	0.478	0.351
[Equation	median	1.595	1.246	0.790	0.546	0.409
(3.1)]	current	1.638	1.178	0.669	0.389	0.361
	q.a.r.	6.702	3.042	2.719	0.788	
Scaled	q.r.w.	6.482	2.950	2.724	0.793	
error	mean	3.450	2.810	2.066	1.458	1.083
[Equation	median	3.615	2.857	2.035	1.529	1.146
(3.2)]	current	4.766	3.245	1.896	1.466	1.257
	q.a.r.	1.694	0.914	0.247	0.103	
% error	q.r.w.	1.479	1.107	0.481	0.144	
[Equation	mean	0.456	0.314	0.163	0.066	0.052
(3.3)]	median	0.455	0.326	0.146	0.073	0.052
	current	0.468	0.316	0.206	0.045	0.037

Notes:

[1]The computation of average absolute error is described in equations (3.11) and (3.13) in the text.

[2]The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences: equation (2.3) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2.4) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

Table 5

Pairwise Differences in Forecast Accuracy[1]
Among the Mean, Median and Most Current Analyst Forecasts,[2]
for Five Forecast Horizons[3]

Panel A: t-Statistics[4] on Differences in Average Absolute Error

Dependent Variable:[5]	Horizon:	240	180	120	60	5
	mean - median	-1.06	-0.98	-1.11	-2.14	-1.62
(3.1)	mean - current	0.11	1.07	1.82	2.83	-0.02
	median - current	1.18	2.05	2.93	4.97	1.60
	mean - median	-0.83	-0.85	-1.12	-1.70	-1.29
(3.2)	mean - current	-0.47	0.60	0.89	1.68	-0.65
	median - current	0.36	1.44	2.01	3.38	0.64
	mean - median	-0.33	-0.28	-0.50	-1.12	-0.82
(3.3)	mean - current	0.07	0.35	0.58	1.77	0.29
	median - current	0.40	0.64	1.08	2.89	1.12

Panel B: t-Statistics[4] on Differences in Average Squared Error

Dependent Variable:[5]	Horizon:	240	180	120	60	5
	mean - median	-0.26	-0.04	0.20	-0.83	-0.59
(3.1)	mean - current	-0.44	0.30	1.06	1.09	-0.10
	median - current	-0.18	0.34	0.86	1.91	0.50
	mean - median	-0.15	-0.07	0.05	-0.15	-0.12
(3.2)	mean - current	-1.22	-0.64	0.26	-0.02	-0.33
	median - current	-1.06	-0.57	0.21	0.13	-0.21
	mean - median	.00	-0.02	0.09	-0.16	0.02
(3.3)	mean - current	-0.01	.00	-0.25	0.46	0.76
	median - current	-0.01	0.02	-0.34	0.61	0.74

Notes:

[1]The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute errors, and Table 4 for the average squared errors. The computations are described in equations (3.10) through (3.15) in the text.

[2]The forecast sources are:
mean - the mean of the available analysts' forecasts.
median - the median of the available analysts' forecasts.

current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

[4]The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

[5]The dependent variables, denoted (3.1), (3.2) and (3.3), refer to equation numbers in the text, and are alternate definitions of the forecast error.

Table 6

Pairwise Differences in Forecast Accuracy[1]
Between Analysts and a Quarterly Autoregressive Model,[2]
for Five Forecast Horizons[3]

Panel A: t-Statistics[4] on Differences in Average Absolute Error

Dependent Variable:[5]	Quarter: / Horizon:	1 / 240	2 / 180	3 / 120	4 / 60
	q.a.r. - mean	5.85	4.15	2.85	-2.36
(3.1)	q.a.r. - median	4.79	3.17	1.74	-4.51
	q.a.r. - current	5.96	5.22	4.67	0.46
	q.a.r. - mean	4.54	2.28	1.82	-3.06
(3.2)	q.a.r. - median	3.71	1.43	0.70	-4.76
	q.a.r. - current	4.07	2.88	2.71	-1.38
	q.a.r. - mean	2.74	2.34	1.55	-0.67
(3.3)	q.a.r. - median	2.41	2.06	1.05	-1.79
	q.a.r. - current	2.81	2.69	2.13	1.11

Panel B: t-Statistics[4] on Differences in Average Squared Error

Dependent Variable:[5]	Quarter: / Horizon:	1 / 240	2 / 180	3 / 120	4 / 60
	q.a.r. - mean	5.08	3.16	2.73	-0.22
(3.1)	q.a.r. - median	4.81	3.13	2.93	-1.04
	q.a.r. - current	4.64	3.47	3.79	0.87
	q.a.r. - mean	3.00	0.34	0.99	-1.38
(3.2)	q.a.r. - median	2.85	0.27	1.04	-1.53
	q.a.r. - current	1.79	-0.30	1.25	-1.40
	q.a.r. - mean	1.30	1.11	0.48	0.81
(3.3)	q.a.r. - median	1.30	1.09	0.57	0.65
	q.a.r. - current	1.29	1.10	0.23	1.26

Notes:

[1]The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute errors, and Table 4 for the average squared errors. The computations are described in equations (3.10) through (3.15) in the text.

[2]The forecast sources are:
q.a.r. - a quarterly autoregressive model in fourth differences; equation (2.3) in the text.
mean - the mean of the available analysts' forecasts.
median - the median of the available analysts' forecasts.
current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

[4]The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

[5]The dependent variables, denoted (3.1), (3.2) and (3.3), refer to equation numbers in the text, and are alternate definitions of the forecast error.

Table 7

Pairwise Differences in Forecast Accuracy[1]
Between Analysts and a Quarterly Random Walk Model,[2]
for Four Forecast Horizons[3]

Panel A: t-Statistics[4] on Differences in Average Absolute Error

Dependent Variable:[5]		Quarter: 1 Horizon: 240	2 180	3 120	4 60
	q.r.w. - mean	5.56	4.20	3.92	-1.70
(3.1)	q.r.w. - median	4.50	3.21	2.81	-3.84
	q.r.w. - current	5.67	5.27	5.74	1.13
	q.r.w. - mean	4.75	2.45	2.86	-2.57
(3.2)	q.r.w. - median	3.92	1.61	1.74	-4.27
	q.r.w. - current	4.29	3.05	3.75	-0.89
	q.r.w. - mean	2.68	2.33	2.80	0.32
(3.3)	q.r.w. - median	2.35	2.04	2.29	-0.80
	q.r.w. - current	2.75	2.68	3.37	2.10

Panel B: t-Statistics on Differences in Average Squared Error

Dependent Variable:[5]		Quarter: 1 Horizon: 240	2 180	3 120	4 60
	q.r.w. - mean	4.49	3.26	3.09	-0.38
(3.1)	q.r.w. - median	4.22	3.23	3.29	-1.21
	q.r.w. - current	4.05	3.56	4.15	0.70
	q.r.w. - mean	2.80	0.21	1.00	-1.37
(3.2)	q.r.w. - median	2.65	0.14	1.05	-1.52
	q.r.w. - current	1.59	-0.43	1.26	-1.39
	q.r.w. - mean	1.08	1.46	1.81	1.71
(3.3)	q.r.w. - median	1.08	1.44	1.90	1.55
	q.r.w. - current	1.06	1.46	1.56	2.17

Notes:

[1]The reported numbers are t-statistics on pairwise differences in average absolute or squared forecast error. See Table 3 for the average absolute errors, and Table 4 for the average squared forecast errors. The computations are described in equations (3.10) through (3.15) in the text.

[2]The forecast sources are:

q.r.w. - a quarterly random walk model in fourth differences; equation (2.4) in the text.

mean - the mean of the available analysts' forecasts.

median - the median of the available analysts' forecasts.

current - the most recent forecast from an analyst.

[3]The forecast horizons are measured in trading days prior to the annual earnings announcement.

[4]The degrees of freedom for all reported t-statistics are over 2,000, so they are approximately normal. For a two-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.96 and 2.58, respectively.

[5]The dependent variables, denoted (3.1), (3.2) and (3.3), refer to equation numbers in the text, and are alternate definitions of the forecast error.

Table 8

Summary of Regression Results:
Adjusted R^2 and Regression F-statistic[1] for Regression of EPS Forecast Error on Excess Return[2]

Dependent Variable:	Horizon:	240	180	120	60	5
	R2	.116	.095	.107	.114	.156
Unscaled	F(k-1,N-k)	5.02	4.27	4.79	5.09	4.60
error	k	199	199	199	199	195
[Eqn. (3.1)]	N	5986	6171	6267	6293	3779
	R2	.139	.138	.129	.144	.154
Scaled	F(k-1,N-k)	5.80	5.93	5.61	6.25	4.51
error	k	195	195	195	195	191
[Eqn. (3.2)]	N	5783	5966	6057	6083	3653
	R2	.104	.099	.097	.088	.138
% error	F(k-1,N-k)	4.49	4.37	4.35	4.02	4.08
[Eqn. (3.3)]	k	199	199	199	199	195
	N	5928	6111	6202	6228	3740

Notes:

[1]The reported F-statistics have degrees of freedom k-1 and N-k, where k is the number of estimated parameters, including the intercept, and N is the number of observations. Selected critical points for the F distribution are:

	$\alpha = .001$
F(120,120)	1.77
F(120, ∞)	1.45

[2]The estimated regression model is equation (3.17) in the text.

Table 9

Summary of Regression Results:

Incremental F-statistics[1] for Groups of Parameters,

in the Regression of EPS Forecast Error on Excess Return[2]

Dep. V'ble:		Horizon:	240	180	120	60	5
(3.1)	year	F(k1,N-k)	54.13	36.79	25.17	19.25	2.94
		k1	6	6	6	6	6
	firm	F(k2,N-k)	3.34	3.08	3.87	4.82	4.65
		k2	183	183	183	183	183
	excess return	F(k3,N-k)	6.89	7.33	14.37	3.57	2.18
		k3	5	5	5	5	3
		N-k	5787	5972	6068	6094	3584
(3.2)	year	F(k1,N-k)	48.82	47.56	25.77	19.04	3.47
		k1	6	6	6	6	6
	firm	F(k2,N-k)	4.36	4.54	4.86	6.10	4.61
		k2	179	179	179	179	179
	excess return	F(k3,N-k)	4.71	4.74	8.89	1.64	1.19
		k3	5	5	5	5	3
		N-k	5588	5771	5862	5888	3462
(3.3)	year	F(k1,N-k)	18.94	15.9	18.21	15.47	2.71
		k1	6	6	6	6	6
	firm	F(k2,N-k)	4.08	3.98	3.83	3.74	4.19
		k2	183	183	183	183	183
	excess return	F(k3,N-k)	2.51	3.07	7.28	1.72	0.18
		k3	5	5	5	5	3
		N-k	5729	5912	6003	6029	3545

Notes:

[1]The reported F-statistics test the incremental explanatory power of including groups of parameters in the models. The hypotheses are

discussed in section 5 of the paper. Selected critical points for the F distribution are:

	$\alpha = .05$	$\alpha = .001$
F(3,120)	2.68	5.78
F(3, ∞)	2.60	5.42
F(5,120)	2.29	4.42
F(5, ∞)	2.21	4.10
F(6,120)	2.18	4.04
F(6, ∞)	2.10	3.74
F(120,120)	1.61	1.77
F(120, ∞)	1.43	1.54

[2]The estimated regression model is equation (3.17) in the text.

Table 10

Summary of Regression Results:
Slope Coefficients[1] for Five Forecast Sources,[2]
in the Regression of EPS Forecast Error on Excess Return[3]

(t-statistics[4] are in parentheses)

	Horizon:	240	180	120	60	5
	Source:					
Panel A: Unscaled error [Equation (3.1)]	q.a.r.	0.98 (5.38)	0.96 (5.72)	0.99 (6.46)	0.48 (3.26)	
	q.r.w.	0.29 (1.61)	0.24 (1.44)	0.63 (4.15)	0.18 (1.25)	
	mean	0.14 (0.78)	0.01 (0.04)	0.34 (2.20)	0.14 (0.96)	0.66 (1.68)
	median	0.07 (0.40)	0.07 (0.40)	0.41 (2.68)	0.20 (1.38)	0.77 (1.97)
	current	0.32 (1.75)	0.29 (1.75)	0.53 (3.49)	0.37 (2.49)	0.25 (0.64)
Panel B: Scaled error [Equation (3.2)]	q.a.r.	0.95 (3.18)	1.15 (4.68)	1.25 (5.00)	0.55 (2.25)	
	q.r.w.	0.48 (1.61)	0.33 (1.33)	0.78 (3.11)	0.17 (0.68)	
	mean	0.55 (1.85)	0.07 (0.29)	0.45 (1.80)	0.10 (0.40)	0.49 (0.67)
	median	0.49 (1.65)	0.14 (0.55)	0.53 (2.14)	0.21 (0.84)	0.88 (1.21)
	current	0.73 (2.44)	0.18 (0.72)	0.76 (3.04)	0.43 (1.75)	-0.88 (-1.21)

Table 10 (Continued)

	Horizon:	240	180	120	60	5
	Source:					
Panel C: % error [Equation (3.3)]	q.a.r.	0.34	0.38	0.35	0.15	
		(2.74)	(3.58)	(4.26)	(2.36)	
	q.r.w.	0.18	0.15	0.27	-0.01	
		(1.47)	(1.42)	(3.23)	(-0.15)	
	mean	0.12	0.05	0.15	0.02	-0.00
		(0.95)	(0.49)	(1.84)	(0.25)	(-0.01)
	median	0.11	0.06	0.16	0.03	0.10
		(0.88)	(0.53)	(1.92)	(0.47)	(0.72)
	current	0.16	0.10	0.22	0.11	0.02
		(1.34)	(0.96)	(2.65)	(1.83)	(0.14)

Notes:

[1]Separate slope coefficients are estimated for each of the forecast sources. The statistical significance of the correlation between forecast errors and excess returns is measured by the t-statistic on the slope coefficient.

[2]The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (2.3) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2.4) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

[3]The estimated regression model is equation (3.17) in the text.

[4]The t-statistics are approximately normal. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

Table 11

Pairwise Differences in the Association between Forecast Errors and Excess Returns,[1]

Panel A: t-Statistics[2] on Differences between Quarterly Model (2.3) and Other Forecast Sources[3]

Dependent Variable:[4]	Quarter:	1	2	3	4	
	Horizon:	240	180	120	60	5
	q.a.r. - q.r.w.	2.69	3.08	1.68	1.47	
	q.a.r. - mean	3.28	4.08	3.09	1.68	
(3.1)	q.a.r. - median	3.55	3.82	2.74	1.37	
	q.a.r. - current	2.59	2.85	2.16	0.56	
	q.a.r. - q.r.w.	1.12	2.41	1.37	1.15	
	q.a.r. - mean	0.95	3.15	2.32	1.35	
(3.2)	q.a.r. - median	1.09	2.97	2.08	1.03	
	q.a.r. - current	0.53	2.85	1.43	0.36	
	q.a.r. - q.r.w.	0.91	1.55	0.74	1.84	
	q.a.r. - mean	1.28	2.22	1.75	1.54	
(3.3)	q.a.r. - median	1.33	2.19	1.70	1.38	
	q.a.r. - current	1.00	1.88	1.17	0.39	

Panel B: t-Statistics[2] on Differences between the Most Current and the Mean and Median Analyst Forecasts[3]

Dependent Variable:[4]	Horizon:	240	180	120	60	5
(3.1)	mean - current	-0.69	-1.23	-0.94	-1.12	0.76
	median - current	-0.96	-0.97	-0.59	-0.82	0.97
(3.2)	mean - current	-0.42	-0.30	-0.90	-0.99	1.37
	median - current	-0.56	-0.12	-0.65	-0.67	1.77
(3.3)	mean - current	-0.28	-0.34	-0.58	-1.15	-0.11
	median - current	-0.33	-0.31	-0.52	-0.99	0.42

Notes:

[1]The estimated regression model is equation (3.17) in the text.
[2]The t-statistics are approximately normal. For a one-sided test, the .05 and .01 critical points from the N(0,1) distribution are 1.65 and 2.33, respectively.

[3]The forecast sources are:

- q.a.r. - a quarterly autoregressive model in fourth differences; equation (2.3) in the text.
- q.r.w. - a random walk model with drift in fourth differences; equation (2.4) in the text.
- mean - the mean of the available analysts' forecasts.
- median - the median of the available analysts' forecasts.
- current - the most recent forecast from an analyst.

[4]The dependent variables are transformations of the forecast error, described in equations (3.1), (3.2) and (3.3) in the text.

FOOTNOTES

[1]Differences among analyst composite forecasts are qualitatively similar in a larger sample of firms, not subject to the time-series models' selection bias.

[2]An example of diversification across forecast sources to improve accuracy is discussed by Beaver (1981), where the forecasts are for sports scores.

[3]See Granger and Newbold (1977) for a discussion and review of some evidence, and Figlewski and Urich (1982) for a more recent examination. These studies consider predictions of macroeconomic variables.

[4]From a sample of over 45,000 forecasts on 457 firms in 7 years, when a requirement was imposed that the same analyst produce forecasts for a firm in at least six years, the sample size was reduced to 138 forecasts on 15 firms. This is fewer than two forecasts per firm-year, on average.

[5]This criterion can be criticized for overemphasizing a cross-sectional outperformance, which may be anecdotal given that the series are not independent. I criticize previous studies of analysts' forecasts on these grounds in section 3.2.

[6]"Earnings" and "earnings per share" (or "EPS") are sometimes used interchangeably in this paper. The data consist of forecasts of EPS, and I wish to abstract from the effects of changes in capitalization on the prediction of earnings. When a change in capitalization is announced between a forecast date and a realization, I adjust the forecast by the actual change in capitalization. Moreover, comparisons across years are accomplished by reducing all years to a common capitalization basis.

[7]The results on predictive accuracy and bias were replicated for three other scales: a variant of (3.3) using the standard deviation in place of the absolute deviation; a variant of (3.2) where the sample was censored to exclude negative denominators; and a variant of (3.2) where the sample was censored to exclude denominators smaller than $.20. The results presented in this paper are representative of the larger set.

[8]This discussion does not argue against the existence of firm-specific effects which persist through time. It argues against an explanation for such effects based on unanticipated information.

[9]The subscript i, which indexes the source of the forecast, is suppressed in the following discussion for readability.

[10]The estimation was also done with firm-specific effects in the model. The bias results do not differ from those reported here.

[11]The estimated effects are not the same as the estimated coefficients, because models (3.10) and (3.11) have two sets of effects, firms and years. A simple example will illustrate this. If there were two years and three firms in the sample, then model (3.10) could be estimated with no intercept, using two year dummy variables (DY1 and DY2) and two firm dummy variables (DF1 and DF2):

$$|e_{jt\tau}| = d_{11\tau}DF1 + d_{12\tau}DF2 + d_{21\tau}DY1 + d_{22\tau}DY2 + \xi_{jt\tau}.$$

The "year 1 effect" is the average $|e_{jt\tau}|$ for $t=1$. This effect is not estimated by $d_{21\tau}$. Rather, $d_{21\tau}$ is the average $|e_{jt\tau}|$ for year 1 for the omitted (third) firm. The "year 1 effect" is estimated in this formulation by:

$$\delta_{21\tau} = d_{21\tau} + (1/3)\ d_{11\tau} + (1/3)\ d_{12\tau} \quad .$$

The "firm 1 effect" is estimated by:

$$\delta_{11\tau} = d_{11\tau} + (1/2)\ d_{21\tau} + (1/2)\ d_{22\tau} \quad .$$

The "firm 3 effect" is estimated by:

$$\delta_{13\tau} = (1/2)\ d_{21\tau} + (1/2)\ d_{22\tau} \quad .$$

Since any non-redundant spanning set of dummy variables can be used, the particular linear combinations of coefficients to estimate the firm and year effects depend on the model used.

[12]Dropping the $\alpha_{1ij\tau}$, the firm-specific effects, does not alter the estimates of the slope coefficients $\beta_{i\tau}$ or their statistical significance by a substantial amount. Omitting the $\alpha_{2it\tau}$, however, alters both the estimates and their statistical significance.

[13]An alternative way to model this problem is to include the year and firm effects as "random effects", contributing off-diagonal elements to the covariance matrix of the $v_{ijt\tau}$. Mundlak (1978) shows that the estimate of the slope coefficient $\beta_{i\tau}$ obtained from a model like (3.17), is identical to the GLS estimate which would be obtained if the firm- and year-specific effects, $\alpha_{1ij\tau}$ and $\alpha_{2it\tau}$, were modeled as random effects and included in the covariance matrix.

[14]Brown, Foster and Noreen (1984) analyze a related, but different, dataset, taken from the set of summary statistics which I/B/E/S produces for clients.

[15]Firms announce earnings with remarkable consistency year after year, so choosing fixed lengths of time prior to the announcement date is a fairly accurate means of finding dates that differ by one quarter's earnings. Of the 6218 horizons included in this paper, 13 dates did not fall between the quarterly announcements as intended. The results are not affected by deletion of these

observations.

[16]Results did not differ from those reported here when the value-weighted market portfolio of securities was used as a proxy for the market.

[17]For example, see Dirks and Gross, The Great Wall Street Scandal, especially pp. 252-257. Also see "Bank Analysts Try to Balance their Ratings", WSJ, May 29, 1984, p. 33; and "Picking a Loser", WSJ, September 28, 1983, p. 1.

[18]An alternate method of measuring the association between forecast errors and excess returns, similar to that of Ball and Brown (1968), constructs portfolios based on foreknowledge of the sign of EPS forecast error. That is, a long position is taken in each of the securities for which the forecast error is positive, and a short position is taken in those with negative errors. This procedure, applied to these data, produces results qualitatively identical to those reported here.

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